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Article

An Intelligent Cluster Optimization Algorithm for Smart Body Area Networks

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Abstract: Body Area Networks (BODYNETs) or Wireless Body Area Networks (WBAN), being an important type of ad-hoc network, plays a vital role in multimedia, safety, and traffic management applications. In BODYNETs, rapid topology changes occur due to high node mobility, which affects the scalability of the network. Node clustering is one mechanism among many others, which is used to overcome this issue in BODYNETs. There are many clustering algorithms used in this domain to overcome this issue. However, these algorithms generate a large number of Cluster Heads (CHs), which results in scarce resource utilization and degraded performance. In this research, an efficient clustering technique is proposed to handle these problems. The transmission range of BODYNET nodes is dynamically tuned accordingly as per their operational requirements. By optimizing the transmission range, the packet loss ratio is minimized, and link quality is improved, which leads to reduced energy consumption. To select optimal CHs the Whale Optimization Algorithm (WOA) is used based on their fitness, which enhances the network performance by reducing routing overhead. Our proposed scheme outclasses the existing state-of-the-art techniques, e.g., Ant Colony Optimization (ACO), Gray Wolf Optimization (GWO), and Dragonfly Optimization Algorithm (DFA) in terms of energy consumption and cluster building time.

Keywords: Bodynets; WBAN; clustering; ad-hoc networks; whale optimizer; artificial neural networks; intelligent transportation system

1 Introduction

A Body Area Networks (BODYNETs) or Wireless Body Area Networks (WBAN) is a group of programmable and/or wearable sensors, which also act as a node. These nodes can communicate with each other, with other smart sensors, and devices, e.g., smartphones [1,2]. These sensor nodes are capable to perform several operations besides sensing. Furthermore, they can transmit, receive, store, and compute the data. The interconnection between smart devices like smartphones or Internet of Thing (IoT) devices with Body Sensor Networks (BSNs) show that they can be incorporated with existing and even new networks [3–5]. The infrastructure of BSNs can be cloud-based [6,7] for flexible storage and processing, which helps for both online and offline data analysis processing. The BSNs can be used in various applications; however, m-health applications are probably the most important one. In BSNs, the wireless sensors can be used on skin or garments to continuously and non-invasively monitor the important physiological signals. The extracted signals can be used to detect or monitor some important diseases like cardiovascular and neurodegenerative disorders and can be proved helpful in rehabilitation. These BSNs can also be used in a variety of domains like e-sports, e-wellness, and e-fitness where the aim is to monitor the physical and mental health; e-social where they can monitor the mental and emotional state of a lonely person, and e-factory where these sensors can monitor the employees' safety. Despite having a lot of research in this area, there are still many issues in BSNs technology. These issues include hardware issues, communication issues, software architecture [8], and advanced algorithms for data processing.

By considering the above-mentioned issues, intelligent clustering algorithms can play an important role in WBAN by making it more manageable, scalable, optimized, and by balancing network load. Network clustering means the grouping of nodes using their similarities. The similarity between nodes can be measured by the distance between nodes and the availability of bandwidth. Different clustering algorithms differ from each other based on some grouping rules. The clustering means grouping or collection of nodes and one of the nodes is designated as Cluster Heads (CHs) or cluster node. The cluster size in BODYNET depends on the transmission range. The clusters will be large in case of a large transmission range and it contains more nodes. As the number of clusters is inverse to the transmission range therefore, the number of clusters should be optimized for this problem. Therefore, intelligent node clustering is required, which can give a minimum number of clusters, CHs, and long life of clusters. The more time nodes spend in a cluster, the better will be the networks' performance. The network nodes' clustering is an NP-hard problem and CHs play an important role in this clustering process. The role of CH includes the formation and end of the clusters, topology selection for maintenance, and resource provision to cluster members. CHs also manage the communication for both within the network and with other available clusters in the network. The network performance in this scenario can be considered by the clustering stability which can be measured by the CH change ratio and conversion ratio of cluster nodes to CH.

The rest of this paper is organized as follows: Section 2 presents related work which contains issues, challenges in the development of WBAN routing protocols, and different categories of WBANs routing protocols. Section 3 presents a detailed description of the proposed methodology of WOA. Section 4 presents experimental results and analysis. Section 5 concludes the paper.

2 Related Work

In the last few decades, meta-heuristic approaches such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and ACO are getting popular in the field of computer vision and machine learning. These approaches play an important role in computer science and engineering-related areas because these are flexible enough to apply to the problems of different natures. Many meta-heuristic approaches are deviation free and use random variables to solve different problems. These methods start with a random solution, excluding the calculations for the derivation of search space, which makes them suitable to solve existing problems. Lastly, these algorithms focus on exploring the whole workspace eliminating the local optima problem, which is unsuitable for any kind of problem. The technologies of Wireless Sensor Networks (WSN) and ad-hoc networks are quite mature in the perspective of routing protocols because numerous protocols have been designed in the literature for these two technologies [9]. However, in the case of WBAN, protocols designed for WSNs and ad-hoc networks may not be suitable for implementation due to the special nature of WBANs. Several research challenges related to BODYNETS or WBANs and related applications are highlighted in the literature. These include real-time m-health systems, smartphone-based methods, systems for circadian rhythm estimation for biomedical study, wearable sensor-based methods, and systems for clustering human actions using BODYNETS.

2.1 Issues and Challenges in Development of WBAN Routing Protocols

Due to the unique specifications of WBANs, the development of routing protocols for BODYNETS is quite a difficult and challenging task. Some of the key design challenges are discussed below.

2.1.1 Network Topology

For efficient communication systems, proper network topology must be developed as it affects the communication between devices. It is important specifically for WBANs because of their short transmission range and frequent motion of body parts. In the literature, two approaches are frequently used by the researchers for WBAN applications, which are single-hop and multi-hop communication protocols. In the former approach, the data is sent directly from every node to the destination, while in the later approach, the clustering technique is used [10].

2.1.2 Transmission Range

Due to the short transmission range of sensor nodes, problems like partitioning and disconnections are being faced in WBANs. Also, the choice of the next node for routing becomes limited, so many transmission cycles will be used to carry the packets to the destination that will cause a delay in arrival time and the overall temperature of the network rise. To overcome this problem, researchers proposed some routing protocols such as store and forward routing and communication with the line of sight or non-line of sight [2].

2.1.3 Local Energy Efficiency

Local energy efficiency means a challenge that covers the energy consumption of each node, which ultimately affects the lifetime of the overall network. Energy is more consumed when nodes communicate with each other, and they can use less energy while collecting data through sensing or performing any processing on data. On the other hand, network lifetime is also crucial a parameter for effective communication. Whenever the network's first node expires, it ends the network lifetime. So, protocols designed for WBANs should be able to perform communication through different nodes to avoid battery drainage of nodes [11].

2.1.4 Heterogeneity of Devices

In WBAN, nodes may be heterogeneous depending upon their specifications such as memory consumption and power usage. This heterogeneity leads to some important issues and challenges concerning the Quality of System (QoS) in WBAN [7].

2.1.5 Resource Limitation

In WBANs, there is a limitation of resources such as energy sources, memory or storage, power, and processing capabilities. The bandwidth may also be limited due to some factors like interference and noise [12].

2.1.6 Temperature and Overheating

Sensors are deployed on human body organs where sensitive tissues may be affected by heat emitted by nodes' circuits. Transmission power must be kept low so that body tissues remain undamaged by the heat of these nodes [5].

2.1.7 Privacy and Security

Privacy and security of data in WBAN are more important than data collection. Because, in WSNs or ad-hoc networks, the transmitted data consists of medical information that is very critical [13]. Protocols designed for WBANs must take care of security and privacy concerns [14].

2.2 Categorization of WBAN Routing Protocols

Based on the literature review, several routing algorithms for WBANs have been proposed. These algorithms are classified into five categories that are discussed below in detail.

2.2.1 Routing Protocols Based on Body Posture Movement

In WBAN, the network topology between nodes creates a problem such as disconnection due to the motion of body parts. To solve this issue, some solutions or algorithms have been proposed by the researchers. The solutions developed for this problem are based on a periodically updated cost function. To send data packets from the sending node to the receiving node, the route is chosen based on minimum cost. However, for updating link-state information, a large number of transmissions may be required [15]. Maskooki et al. [16] proposed an algorithm based on opportunistic routing, which incurs the body movement aspect. In this algorithm, the network model consists of two sensor nodes: one on the chest and other on the wrist with an additional relay node on the wrist. Two scenarios emerged in this model due to the motion of the wrist. Firstly, when the wrist is on the front side of the body, this is named as line of sight. In this case, data can be directly sent by the sensor node to the receiving node as they are in line of sight. Secondly, when the wrist is in the backside of the body, this is named as non-line of sight. In this case, the relay node is invoked to help in communication.

Quwaider et al. [17] proposed an algorithm that chooses routes having fewer storage delays based on body posture partitioning to decrease the source to destination delay. This is a multi-point routing technique, which consists of seven biomedical sensors. Two sensors on arms, two on thighs, two on the ankle, and one node on the waist. The node on the right ankle collects all sensing data from all the nodes and transmits to external servers. All these sensors form a mesh topology network that may be divided into one or more partitions. Movassaghi et al. [18] proposed an algorithm called ETPA in which the cost function for the route is calculated based on energy level, power, and temperature of nodes. This protocol provides the high depletion time of nodes that is greatly helpful in long-lasting communications. Quwaider et al. [19] proposed a protocol named DVRPLC, which uses cumulative cost from all sensor nodes to the common receiving node. It follows the PRPLC algorithm that intends to minimize delay in the packets delivery by choosing high likelihood communication paths.

2.2.2 Routing Protocols Based on Temperature Rise Reduction

When the human body lies in the wireless communication paths of sensor devices then some critical issues arise that are heating effects on tissues of body and radiation absorbs by them. As biosensors are implanted inside the human body, they generate electric and magnetic fields and get heated because they consume power. Due to this heat and temperature rise of sensor nodes tissues of the organs may be damaged. Numerous protocols have been proposed in that last decades by research to solve the heating rise issue [15]. Tang et al. [20] proposed an algorithm named Thermal Aware Routing Algorithm. In this protocol routing is performed through sensor nodes having low temperature or heat. All the packets are withdrawn from routes having high-temperature nodes and rerouted to the low-temperature zone. Problem with this algorithm that it does not consider the aspect of reliability. Packet loss may occur in high ratio and network lifetime is also less.

In [21], Bassiouni et al. revised and improved algorithm presented in [11] and presented two algorithms Least Temperature Routing and Adaptive Least Temperature Routing. In these algorithms primary focus is given to avoiding loops by maintaining a list of mostly and recently visited sensor nodes. alter changes the route to the shortest path when the number of predetermined hops is crossed. The main shortcoming of this algorithm is that the temperature of every node must be known to each sensor node that is a major overhead. Bag et al. [21], proposed another routing protocol that is thermal aware. This algorithm was designed for critical data like medical information which is delay-sensitive. It is ensured that while selecting the route, nodes that are declared as hotspots, must not exist in that route so that end to end delivery is not affected by the delay. This algorithm is named Hotspot Preventing Routing (HPR) and works in two phases: The first one is the setup phase in which all nodes share their shortest routes and temperature information. In the second phase, based on information of first phase routing is performed considering that hotspot nodes are not involved.

If we compare all these algorithms for the delivery delay and temperature rise than a conclusion can be made that HPR [5] outperforms all others in the reduction of delivery delay and temperature rise [22].

2.2.3 Routing Protocols Based on Cross Layers

In this category routing protocols developed for WBAN intends to solve the challenges and issues related to both layers network and MAC layer to improve the lifetime and performance of network [13]. Several researchers proposed their algorithms to help in this context. Braem et al. [23] proposed an algorithm Wireless Autonomous Spanning Tree Protocol (WASP). In this algorithm creation of WASP cycles involves division of time axis so that incorporation of medium access can be guaranteed. Spanning tree is generated for efficient traffic routing so that minimum energy may be consumed and to improve the high throughput. An improved version of WASP [23] is presented by Braem et al. [24] and named as CICADA. This algorithm is based on multi-hop MBANs specially designed for TDMA scheduling. It provides two-way communication and enhances the reliability.

In [12], the authors proposed a protocol known as TICOSS in which improvement in the MAC layer protocol IEEE 802.15.4 is proposed by improving it in three aspects. It helps in minimizing energy consumption by using the nodes' different periods of being active and inactive, reduction of collisions of packets and helps in carrying a packet to the coordinator. All these cross-layered routing protocols provide low energy consumption and high throughput, but they lack high performance when considering the scenarios in which the body is in motion and have high path loss. If comparative analysis is conducted, a conclusion can be made that WASP [23] provides low energy consumption but inefficient in selecting two-way communication and standard link quality. TICOSS [16] is better than WASP from the perspective of low energy consumption and delivery delay [11].

2.2.4 *Routing Protocols Based on Quality of Service*

This class provides routing protocols that incorporate the modularization technique. Different modules of QoS metrics are created and combined to give high throughput from the perspective of reliability, delivery delay, and delivery ratio. The modules mainly generated are related to energy efficiency, sensitivity in reliability and delay [17]. A routing service framework based on the QoS approach is proposed in [25] that intends to provide routing services based on priority and gives QoS support to users. Functionalities provided by this framework include route selection based on QoS metrics, giving prioritization to packets, providing feedback about the condition of the network, and network load balancing. Liang et al. [26], proposed a QoS based routing algorithm named RL-QRP that uses geographic information and Q learning algorithm. In this protocol route is selected based on experience and reward information. The primary focus of this algorithm is minimizing delivery delay and maximizing the packet delivery ratio. Q learning algorithm assigns each node a positive or negative reward based on their transmission of the data packet. This reward information of each node is then broadcasted to neighbor nodes that help in the decision making of route selection for each node. In [27], the authors presented another QoS based modular algorithm named LOCALMOR that keeps in consideration the nature of data. Transmitted data is segregated as normal data, reliability sensitive data, crucial data, and delay-sensitive data. Four different modules are created to handle this divided data power efficiency module, delay-sensitive module, neighbor manager module, and reliability sensitive module. Based on comparative analysis this may be concluded that these routing protocols do not consider energy consumption which is a very critical aspect of Wireless Body Area Network [7,12].

2.2.5 *Routing Protocols Based on Clustering*

This class of routing protocols consists of network protocols that incorporate cluster formation. All the sensor nodes in the network are grouped into different clusters. One sensing node in each cluster is given responsibilities of collecting data from all nodes in that specific cluster and transmit to the other clusters or sinks. This primary node with responsibilities is called CH. CHs are selected through some metrics. CH is used so that direct communication links from sensing nodes to the sink of data can be reduced. However, the selection of CH is a major overhead [13].

Authors of [20], proposed an algorithm named Any Body that tends to reduce the number of direct communication links to the sink. Previous approaches than this algorithm supposed that all sensing nodes must be in the vicinity of the sink for communication, but this problem is solved by this algorithm by introducing CHs in each cluster. Reliability and energy consumption are not considered in this approach. Authors of [28], proposed another improvement in this domain named Hybrid Indirect Transmission (HIT). Analysis shows that HIT provides high energy efficiency, low network delay, and a high lifetime of network. Both cluster-based routing algorithms for WBAN provides a reduction of power consumption by reducing the number of communication links. The main advantage of Anybody [20] is that number of clusters remains constant even number of nodes is increased.

The use of the evolutionary algorithm s for clustering in other types of ad-hoc networks is also very popular. For instance, another swarm-based technique [29] projected to VANETs for optimal routing solutions. It used the ACO approach and compared it with comprehensive learning particle swarm optimization (CLPSO) and multi-objective particle swarm optimization (MOPSO) [30]. It performed optimally than two existing techniques providing a minimum number of CH's for various network scenarios. But still there is a gap in providing a minimum number of clusters to provide more enhanced VANET services. Similarly, recently proposed protocols like [31,32] both are based on SI techniques namely dragonfly and grey wolf optimization algorithms. Individually these protocols performed better as compared to present techniques CLPSO, MOPSO [33] and ACO [34]. Similarly, GWOCNET [31] and CAVDO [32] have been proposed for the clustering of vehicular nodes on the highways.

3 Methodology

It is observed that each routing protocol does not cover all the vital parameters for communication, rather than they focus on some specific parameters. For instance, routing protocols based on temperature rise mainly focus on the reduction of temperature of nodes and select routes based on hotspots. It does not take into consideration the motion of the body and energy efficiency. The case with all other routing protocols is the same that they omit some key parameters of WBAN and focus on a specific one. The demand for the development of improved routing protocols is vital, considering all the key parameters of WBAN communication. However, the complexity of this problem also falls in the class of the NP-Hard problem. Finding an efficient solution that incorporates all the challenges and issues of WBAN communication is not possible in polynomial time with a deterministic algorithm. Even if the solution is found and someone says for any protocol that this is the best solution, it cannot be verified that the said solution is the best one.

In the proposed framework, an intelligent clustering approach is employed to optimize the routing of data packets throughout the WBANs so that the network becomes more optimized, manageable, and scalable. Clustering in WBAN means, based on some similarities and dissimilarities, WSNs implanted in the human body are grouped to accomplish some specific goals. Some parameters are used to judge the similarity and dissimilarity of nodes like direction, speed, the distance among nodes, and transmission range. Clustering is a technique that is influenced by rules and regulations. In this method, clusters are formed by making groups of sensor nodes where each group one-member node is selected as CH. The selected CH can perform functions like cluster formation, gathering data from all nodes within the cluster, the transmission of the data to other CHs, efficient routing of data packets within and outside the cluster, supplying resources to the member nodes, network maintenance, and termination of the cluster.

In contrast to the clustering approach, if other routing approaches are analyzed in which every node directly communicates to the external server or side unit used in the infrastructure, communication may be impaired. More specifically, if the crowded environment (football match, concerts, Hajj, or big gathering) is concerned in which a lot of people carry a lot of sensor nodes for monitoring then network accumulators may be chocked due to heavy traffic. This is because every node is sending data packets and there is a huge load on side units to manage that incoming and outgoing traffic, so communication may be disturbed. On the other hand, if the clustering approach is used, then only CHs communicate with the side units from each cluster thus, communication links become reduced that results in a reduction of bandwidth.

For efficient communication between nodes, clustering is performed through an evolutionary algorithm. The flow chart of the proposed scheme is shown in Fig. 1. The idea of evolutionary algorithms states that from the given population of individuals, the fittest one will survive. Some candidate solutions are created based on a maximized function. This maximized function is an abstract measure or threshold, which provides more significant results. Based on this fitness measure, the best candidate solution is chosen, which will then be used as a basis for finding the next better solution. Some operations are carried out on these candidate solutions like recombination and mutation. In recombination, a new solution (child) is created by applying an operator to two candidate solutions (parents). In mutation, a new solution is created using a single candidate solution by applying mutation. This process continues iteratively until a sufficient solution is identified. Through this process, one can find the most optimal solution to the defined problem.

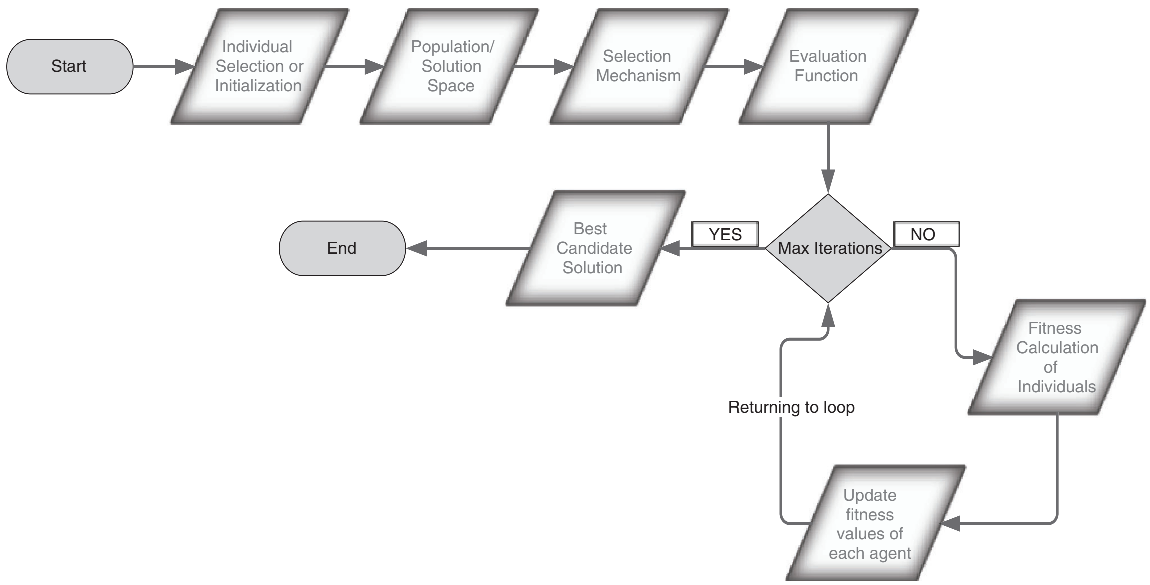

Figure 1: Flow chart of the proposed methodology

3.1 Workflow of Evolutionary Algorithms

Evolutionary algorithms consist of a set of components that must be incorporated while defining these algorithms. These components are as follows:

a. Representation: In representation, individuals within evolutionary algorithms are defined.
b. Evaluation Function: A fitness function or maximized function is identified, which serves as a basis for facilitating improvements. This is the threshold that must be met or used to measure solutions validity.
c. Population: It holds all the possible solutions.
d. Parent Selection Mechanism: Solutions that can become base or parent for the next generation are identified.
e. Variation Operators: Two variation operators, mutation, and recombination, are used to select the new solutions from the old ones.

3.2 Whale Optimization Algorithm

Whales are known to be fancy aquatic entities. They are observed to be the world's biggest mammals. An adult whale continues to grow up to 30 m in length and the weight is around 180t approximately. Major species of whales are seven in number, which includes killer, Minke, Sei, humpback, right, finback and blue, and are categorized as predators. These giant mammals barely sleep as their breathing mechanism is directly associated with the ocean. An interesting fact about whales is that the half portion of the brain is occupied for sleeping purposes and they are super-intelligent creatures with emotions as well.

According to the research done by Hof and Van Der Gucht, whales possess cells in particular portions of their brains, which are almost identical to spindle cells in humans. Spindle cells found in the human brain are usually accountable for decision making, judgments, emotional fluctuations, and other social behaviors. It is correct to say that spindle cells in human beings are distinctive in comparison to other living beings and distinguish them from other creatures. Whales are found to have two times of these cells in number than an adult human. This is the principal cause of smartness in whales. Studies have proved that a whale can think, learn, decide, communicate, judge, and also have sentiments. Killer whales can even establish their dialect. However, all emotional states and smartness are on a lower level compared to humans. The social behavior of whales also forms an interesting pattern. They can live alone and in groups as well but are observed in the latter pattern mostly. Killer whales are capable of living in a family for their entire life span.

Humpback whales (*Megaptera novaeangliae*) are recorded to be one of the biggest baleen whales. An adult whale of this specie is as big as the size of the school bus and they like krill and small fish herds as their prey as shown in Fig. 2. Humpback whales catch their prey is a unique way. Their hunting behavior is termed as bubble-net feeding technique. These whales normally hunt group of krill or tiny fishes, which are closer to the water surface. This is foraging behavior and it is performed by making particular kinds of bubbles in a circle or 9-shaped path as represented in Fig. 2. They recorded 300 tag-derived bubble-net feeding events of nine different humpback whales. Two activities associated with bubble were found and they were named as 'upward-spirals' and 'double-loops.' In the first activity, humpback plunge 12 m down and then create spiral-shaped bubbles surrounding the prey. After that they swim to the water surface. The second activity has three stages named as coral loop, lobtail and capture loop. It is noteworthy that bubble-net feeding is a distinctive behavior that is only observed in humpback whales. In this research work, a spiral bubble-net feeding maneuver is mathematically modeled to perform the optimization.

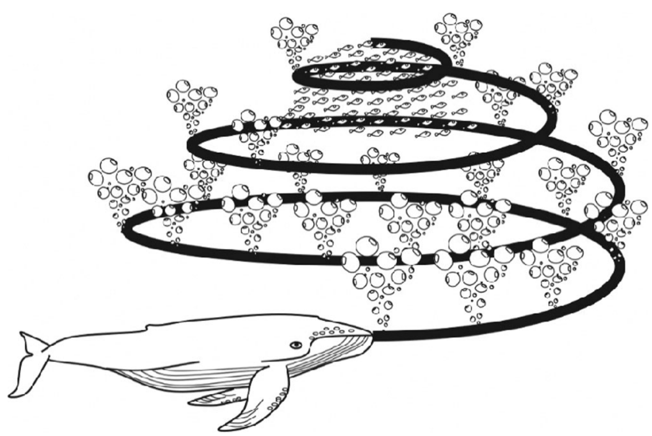

Figure 2: Humpback whales making bubble nets

3.3 Mathematical Model of Optimization Algorithm

This section deals with the mathematical modeling of encircling prey, spiral bubble-net feeding maneuver and prey searching:

3.3.1 Encircling Prey

Humpback whales sense the location of their targeted prey and encircle them. Since the position of the optimal design in the search space is not known, the WOA assumes that the current best candidate solution is the target prey or is close to the optimum. Once the best search agent is established, other search agents update their locations according to the best search agent. The equation mentioned below shows this behavior.

$$\vec{D} = \left| \vec{C} \cdot \vec{X}^* (t) - \vec{X} (t) \right| \tag{1}$$

$$\vec{X} (t+1) = \vec{X}^* (t) - \vec{A} \cdot \vec{D} \tag{2}$$

Here t shows current iteration, $\vec{\boldsymbol{A}}$ and $\vec{\boldsymbol{C}}$ are coefficient vectors, $\boldsymbol{X^*}$ shows position vector of the most optimal solution found so far, $\vec{\boldsymbol{X}}$ is the position vector, $| \, |$ is absolute value and '$\cdot$' is the element-by-element multiplication. $\boldsymbol{X^*}$ must be updated during every iteration if a better solution is found. The vectors $\vec{\boldsymbol{A}}$ and $\vec{\boldsymbol{C}}$ can be calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{4}$$

$\vec{\boldsymbol{a}}$ is linearly decreased from 2 to 0 during iterations in exploration and exploitation phases and $\vec{\boldsymbol{r}}$ is a random vector in $[0, 1]$.

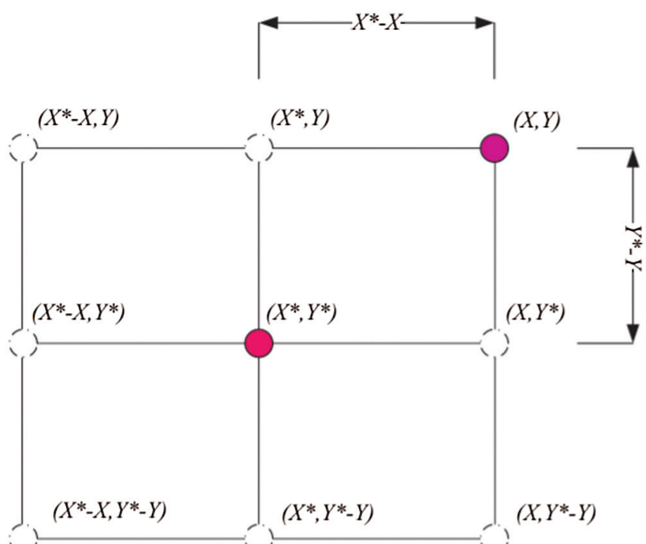

Figure 3: Position vectors along with possible next locations in two dimensions (2D)

Fig. 3 shows the justification behind Eq. (2) for the sake of a two-dimensional problem. The location of $(X, \ Y)$ of the search agent can be updated by the location of the best record (X^*, Y^*), which is currently found. Various positions around the best agent can be obtained for the current location by managing the values of vectors $\vec{A}$ and $\vec{C}$. The possible updating position of search agent in three-dimensional space are discussed in Fig. 4. Any point of search space located among key-points can be reachable once the random vector ($\vec{r}$) is determined (Fig. 3). That is why Eq. (2) permits each search agent to update its location in the neighborhood of the current optimal solution and further simulates encircling the prey.

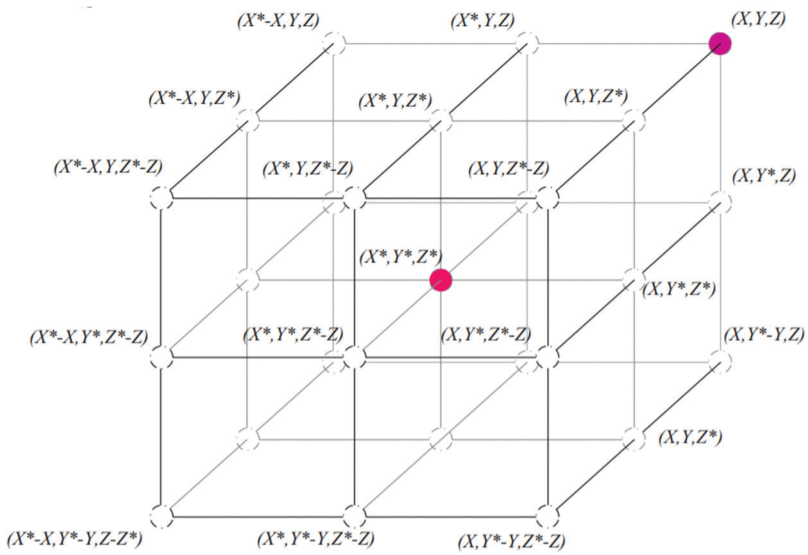

Figure 4: Position vectors along with possible next locations in three dimensions (3D)

Extension of this approach is implied to search space having n dimensions and search agents continue their movement in hyper-cubes around optimal solution acquired till that time. It has been mentioned previously that humpback whales also hunt their prey with bubble-net strategy and this approach is mathematically calculated as follows.

3.3.2 Bubble-Net Attacking Method (Exploitation Phase)

Two methods are suggested for mathematical modeling of bubble-net behavior shown by humpback whales.

Shrinking Encircling Mechanism. This behavior is attained by minimizing the value of $\vec{a}$ in Eq. (3). The range to which $\vec{A}$ is fluctuated is also minimized by $\vec{a}$. It can be said that $\vec{a}$ is a random value in the interval $[-a, a]$ where a is minimized from 2 to 0 over a certain set of iterations. Setting random values for $\vec{A}$ in $[-1, 1]$, the new position of a search agent can be determined anywhere among the actual position of agent and position of current best agent. Fig. 5 represents attainable positions from (X, Y) to (X^*, Y^*), which are reached by $0 \leq A \geq 1$ in a two-dimensional space.

Spiral Updating Position. This technique calculates the distance among the whale's location (X, Y) and prey's location (X^*, Y^*). Afterward, a spiral equation is created between the two positions to depict the helix-shaped movement of humpback whales as mentioned below:

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot cos(2\pi l) + \vec{X} * (t) \quad (5)$$

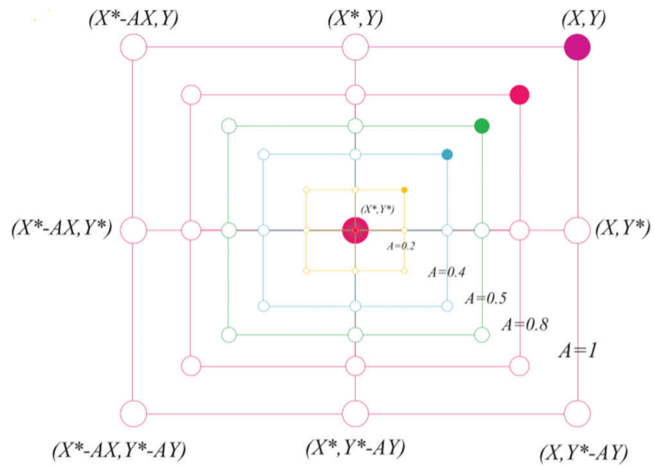

Figure 5: Shrinking encircling mechanism in bubble-net search

Here $\vec{\boldsymbol{D}}' = |\vec{\mathrm{X}}^*(\mathrm{t}) - \vec{\mathrm{X}}(\mathrm{t})|$ and it shows the distance of ith whale to prey (most optimal solution attained so far), b is considered as a constant to determine the shape of a logarithmic spiral, l is a random number in $[-1, 1]$. Humpback whales swim in the surroundings of their targeted prey in circle and spiral-shaped path as well. They show two simultaneous behaviors and to model them, we suppose that there exists a probability of 50% of both actions being exhibited by them during optimization. The mathematical model is mentioned below:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & if\, p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot cos(2\pi l) + \vec{X}^*(t) & if\, p \geq 0.5 \end{cases} \tag{6}$$

where p is a random number between $[0, 1]$. Humpback whales also look out for prey randomly. For this kind of search, the mathematical model is discussed below.

Search for Prey (Exploration Phase). Similar mechanism based on modification of vector $\vec{\mathrm{A}}$ can be exploited for prey searching (exploration). Humpback whales also perform random searches in accordance with their respective positions. We can use $\vec{\mathrm{A}}$ with random values greater than one or less than -1 to get the search agent in moving the state away from reference whale.

Unlike the exploitation phase, the position of the search agent is updated in this phase according to the randomly picked agent. This approach and $|\vec{\boldsymbol{A}}| > \mathbf{1}$ focus on exploration and allow the WOA algorithm to conduct global search. The mathematical model is mentioned below:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_{rand}} - \vec{X}\right| \tag{7}$$

This algorithm begins with a set of random solutions. In all iterations, search agents update their positions with either randomly picked search agent or best solution acquired till that time. The parameter is minimized from 2 to 0 so that exploration and exploitation can be accommodated. A random search agent is picked when $|\vec{\mathrm{A}}| > 1$. However, the most optimal solution is chosen when $|\vec{\mathrm{A}}| < 1$ for updating the locations of search agents. WOA can switch among spiral and

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A} \cdot \vec{D} \tag{8}$$

where, $\overrightarrow{X_{rand}}$ is a random position vector picked from the existing population. Some possible positions of a particular solution with $\vec{A} > 1$ are mentioned in Fig. 5. circular movement depending on the value of p. On reaching the satisfactory termination criteria, WOA terminates. From a theoretical point of view, it can be said that WOA is a global optimizer as it incorporates both exploration and exploitation capabilities. Moreover, the proposed hyper-cube technique determines a search in the neighborhood of the optimal solution and allows other search agents to make use of the best record at present in that domain. Adaptive variation of search vector A allows this algorithm to transit between exploration and exploitation (by minimizing A, some iterations are specified for exploration $|\vec{A}| \geq 1$ and others are for exploitation $|\vec{A}| < 1$) without any difficulty. It is also noteworthy that WOA has only two major parameters that require adjustment (A and C). In this research work, the amount of heuristics and the number of internal parameters are minimized and therefore, ended up implementing the basic category of WOA algorithm. However, hybridization with evolutionary search schemes can be the domain of future work.

4 Experimental Results and Analysis

The simulation parameters have been presented in Tab. 1. In this section, the results are presented from different perspectives like grid size, transmission range, and number of nodes.

Table 1: Simulation parameters

Parameters	Values
Population size (particles)	100
Maximum iterations	150
Inertia weight, W	0.694
Lower bound (lb)	0
Upper bound	100
Dimensions	2
Transmission range	1–10 m
Mobility model	Random waypoint
Simulation runs	10
W1 (weight of first objective function)	0.5
W2 (weight of second objective function)	0.5
Nodes	20–160

The experiments are conducted on MATLAB for different grid sizes and the results are compared with ACO, GWO, and DFA. The number of clusters are formed against different transmission ranges from 1 to 10. The simulations are also carried out for different number of nodes 20, 40, 60 and 80. The WOA shows the minimum cost for all the number of nodes. The graphical results in Figs. 6 and 7. show the superiority in terms of cost reduction for various transmission ranges for 100 m × 100 m grid size. The results presented in Fig. 8. is for 200 m × 200 m grid size. These results also show that the proposed algorithm is the most cost-effective algorithm for communication. There is a distinctive relationship between the transmission range and the number of clusters. The parameters for both the number of clusters and transmission range are inversely proportional to each other, which means that by decreasing the transmission range, the number of clusters of the entire network increases and vice versa. The number of clusters also have an impact on network resources, which means that the increase in the number of clusters increases the required resources.

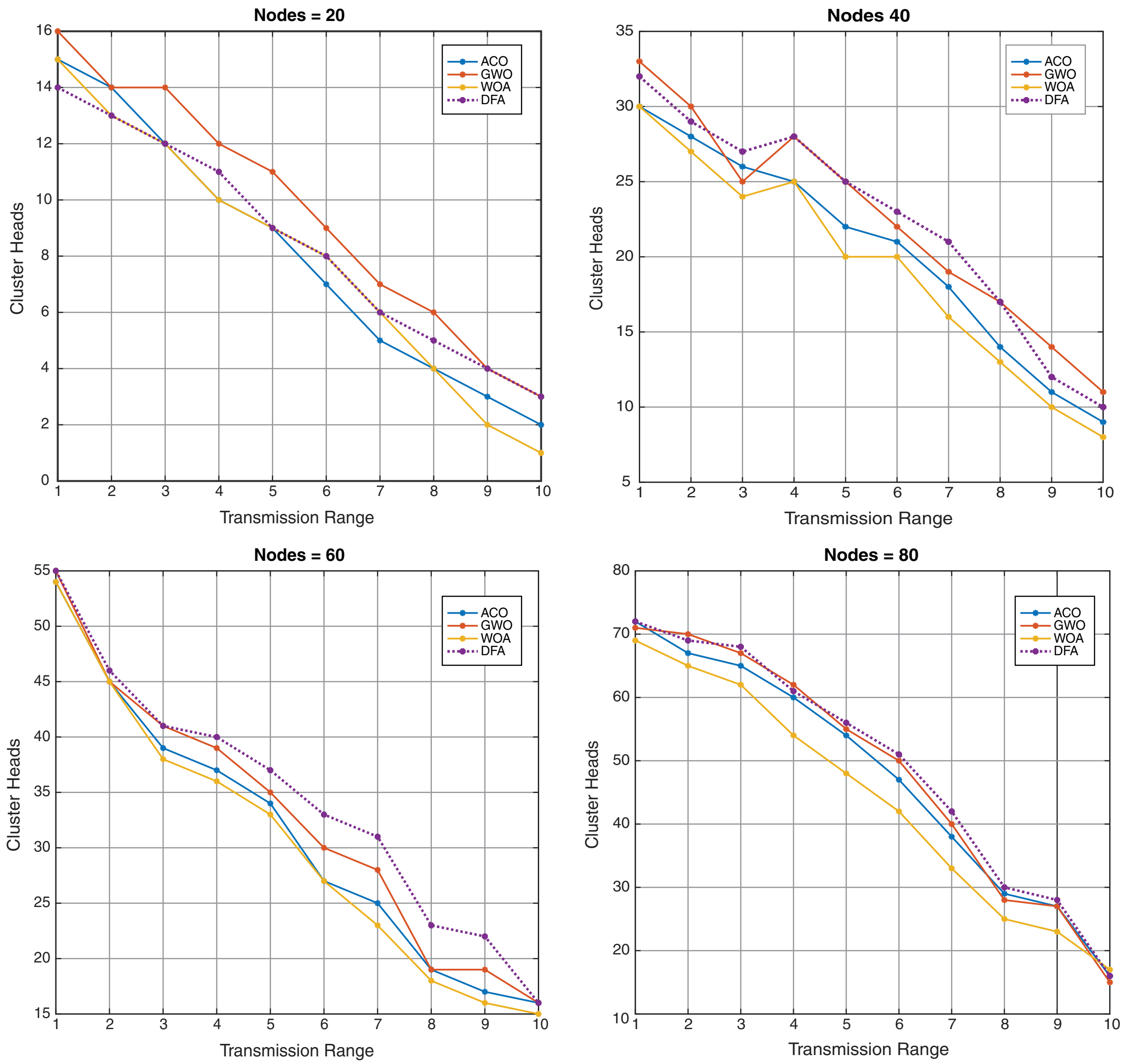

Figure 6: Transmission range *vs*. CHs for nodes 20–80 grid 100 m $\times$ 100 m

Another experiment is conducted considering 300 m $\times$ 300 m grid size for the 20 to 60 nodes. The results presented in Fig. 10 also show that the proposed WOA still performs better compared to other algorithms for the given scenarios. It can also be observed from the results that the proposed algorithm optimizes the routing by efficient clustering, which reduces the number of hopes for network communication. This ultimately minimize the packet delay and routing cost. This is because fewer resources will be required for a lesser number of clusters. All the experiments compare the results of the proposed WOA with other methods for fallout. Figs. 6–10 shows that

WOA considerably show better results as compared to other mentioned algorithms. The results justify the relationship between transmission range and the number of clusters, the resources required for the number of clusters. This optimization ultimately reduces the routing cost for the network.

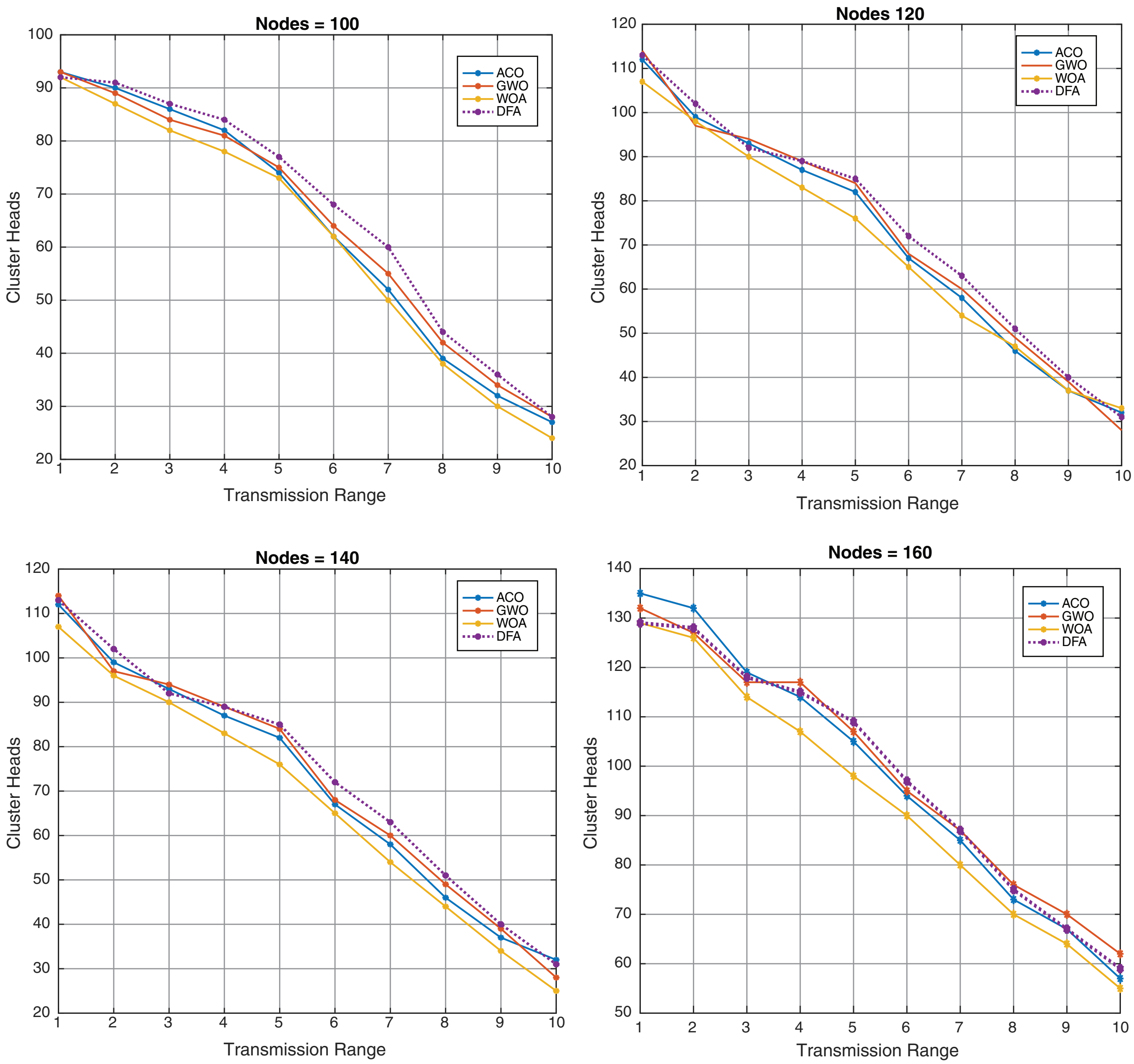

Figure 7: Transmission range *vs*. CHs for nodes 100–160 grid 100 m × 100 m

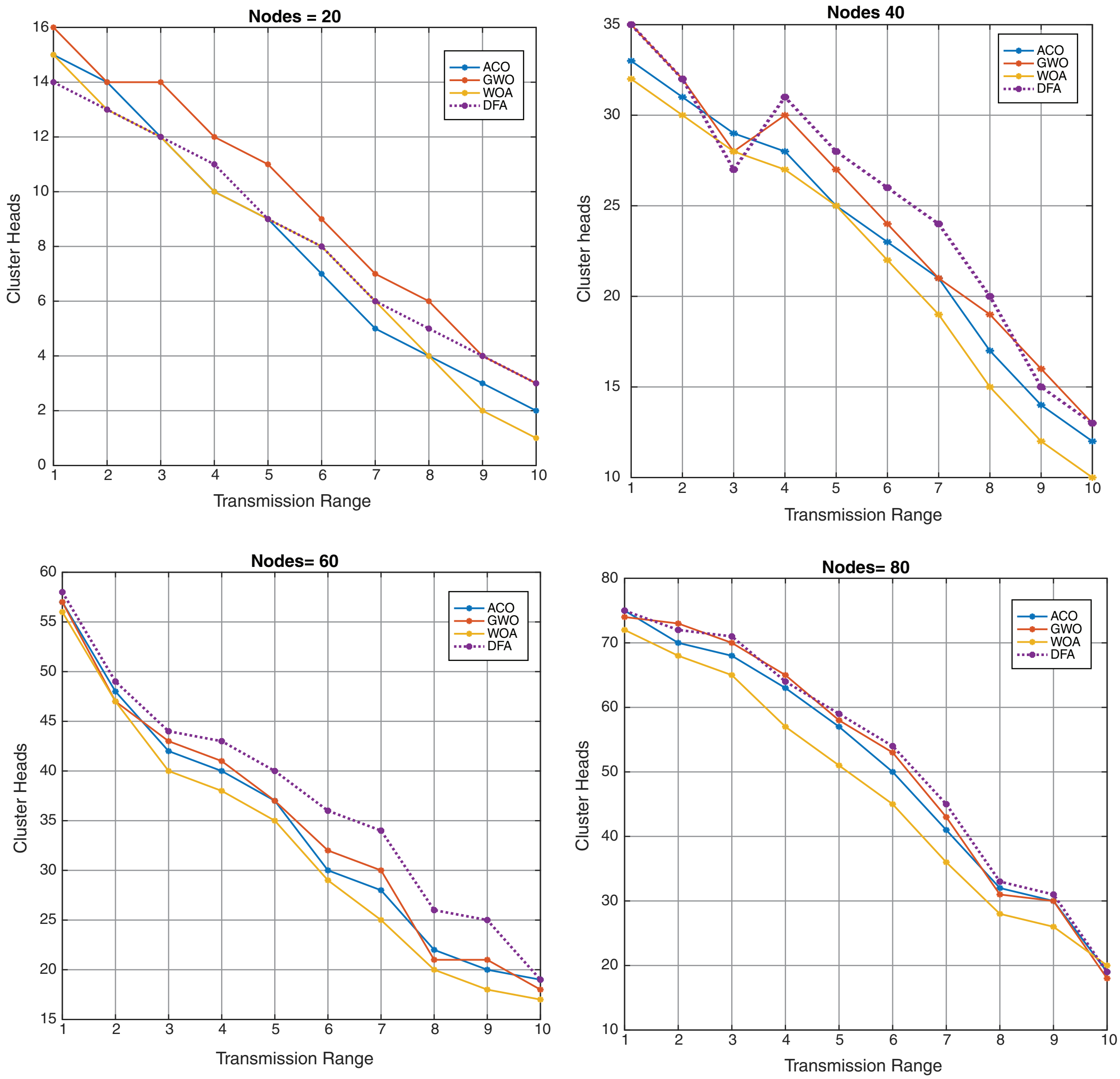

Figure 8: Transmission range *vs*. CHs for nodes 20–80 grid 200 m × 200 m

The results in Fig. 6 shows that WOA form fifteen clusters initially and then move to fifty-four clusters for 60 nodes, which shows better performance in terms of optimized clusters for transmission range of 1 meter. The detailed analysis for 200 m × 200 m grid is shown in Fig. 8. Fig. 8 shows that the proposed algorithm performs better than other mentioned algorithms. Fig. 10 shows the results for 300 m × 300 m grid for 1 to 10 transmission ranges. By comparing the results of Figs. 8 and 9, it is evident that number of clusters increases by increasing grid size. This shows a direct relation between grid size and the number of clusters. The next experiment is conducted with 200 m × 200 m grid size and taking transmission range from 1 to 10. The distance between nodes increases by increasing the grid size, which shows a direct relation and ultimately increases in grid size isolate the nodes. The increase in a high number of isolated nodes, which results in the maximum number of clusters for each mentioned algorithm. It can be observed from Figs. 6 and 7 that the algorithms GWO and WOA produced the same number of clusters. However, the proposed WOA still performs better compared to the other algorithms and reduces the number of clusters by 46%. Therefore, we can conclude that the relationship between the transmission range and the number of clusters is inversely proportional. Therefore, the number of clusters decreases by increasing the transmission range. This is because many clusters are required to cover a large area. However, it is still observed that the proposed algorithm produced a smaller number of clusters compared to other mentioned algorithms. The overlap of the proposed and other mentioned algorithms on some points is due to the randomness, which is because of the random nature of evolutionary algorithms.

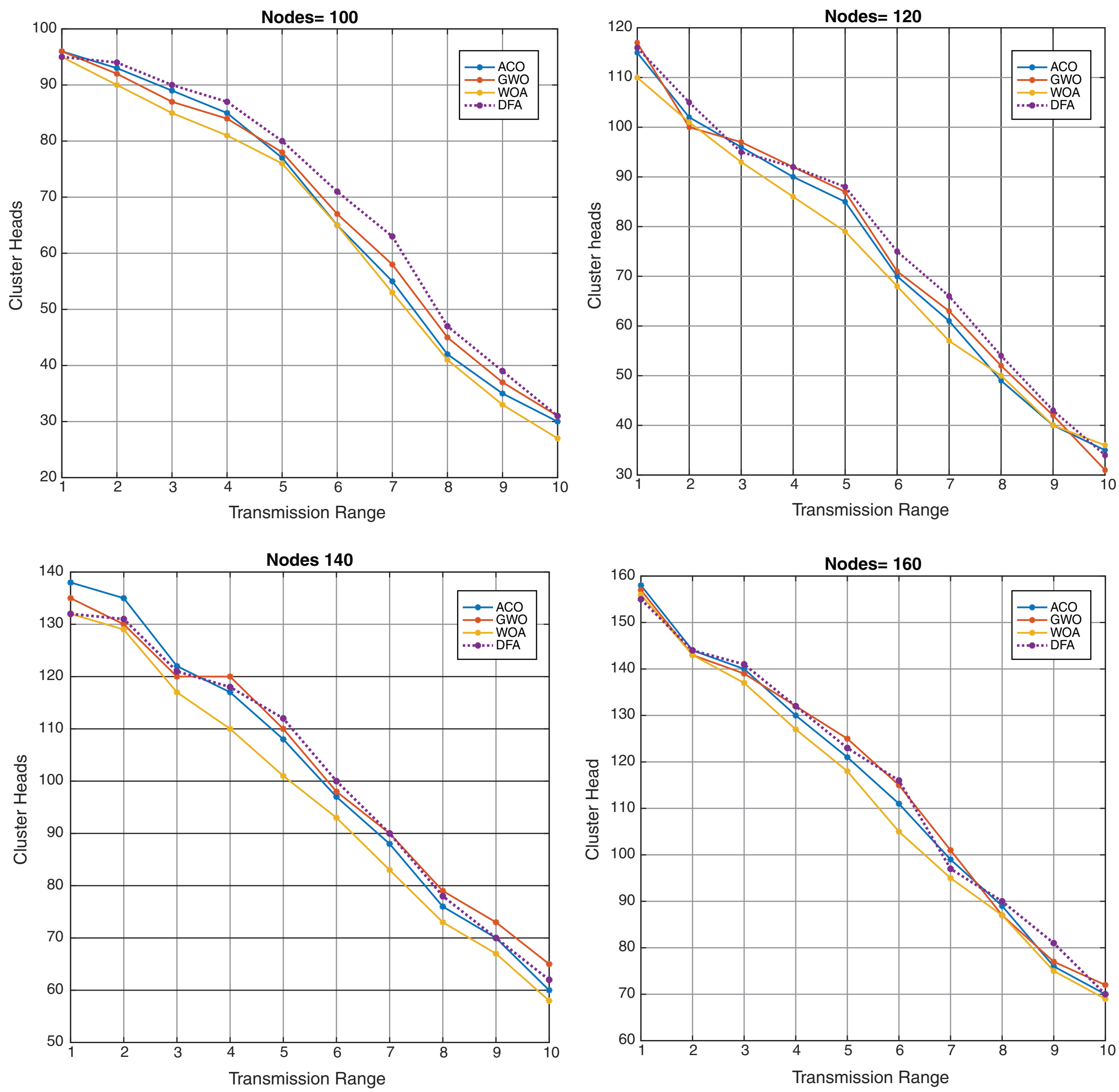

Figure 9: Transmission range *vs*. CHs for nodes 100–160 grid 200 m × 200 m

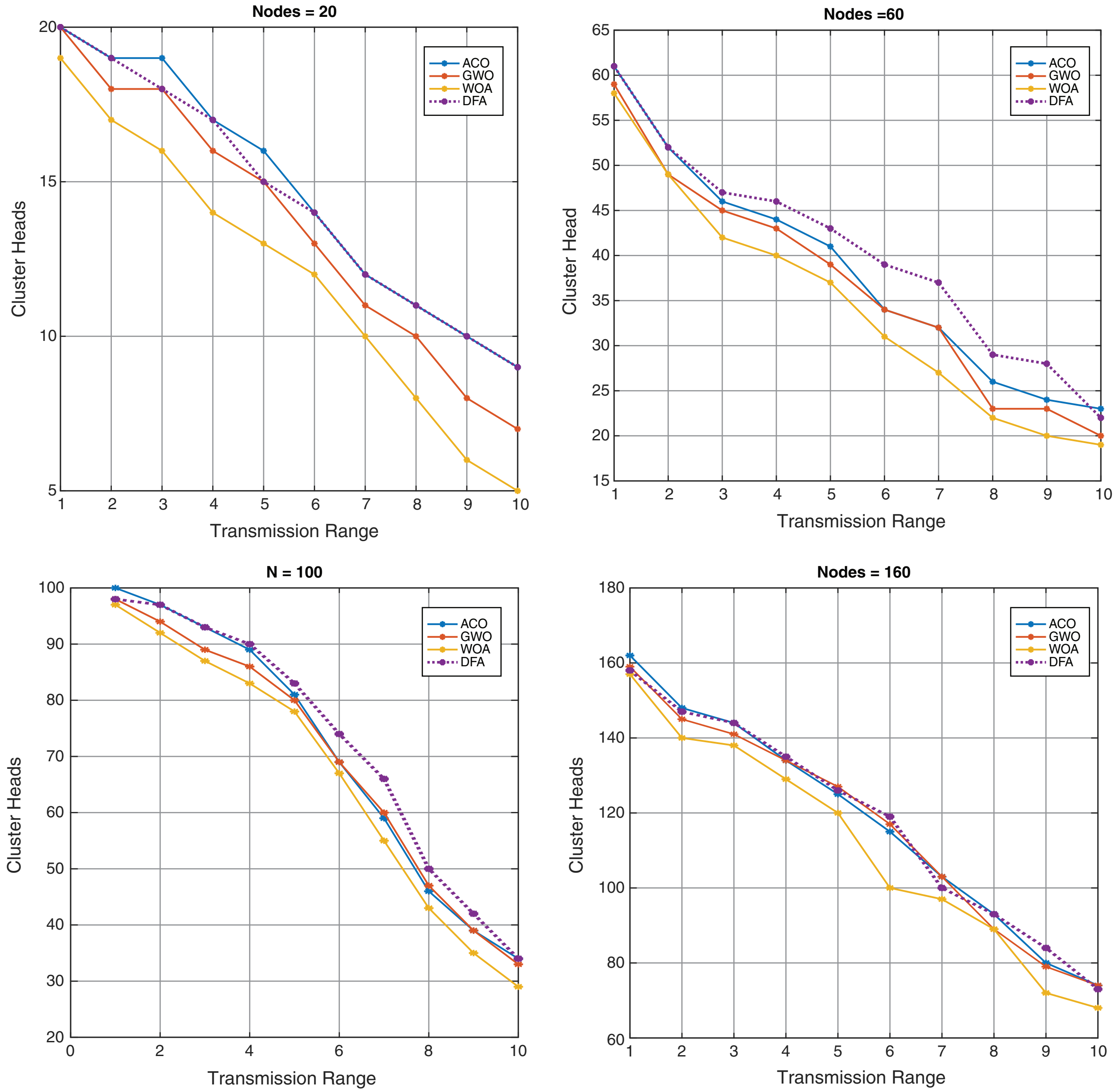

Figure 10: Transmission range *vs*. CHs for nodes 20–160 grid 300 m × 300 m

5 Conclusion

There are various BODYNETs algorithms proposed in the literature for cluster optimization. These algorithms have their strengths and weaknesses for network resource utilization. The proposed work for node clustering is inspired by the nature of whales. It performs better than the GWO, ACO, and DFA in terms of the number of CHs for varying transmission ranges, grid size, and number of nodes. It reduces the communication cost of the network by minimizing the number of clusters. This minimized number of clusters also leads to less resource requirements in BODYNETS. In the future, we intend to design an objective function based on user requirements.

This can further be extended to multi-objective functions as well. The proposed work can also be modified for dynamic transmission ranges for nodes.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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